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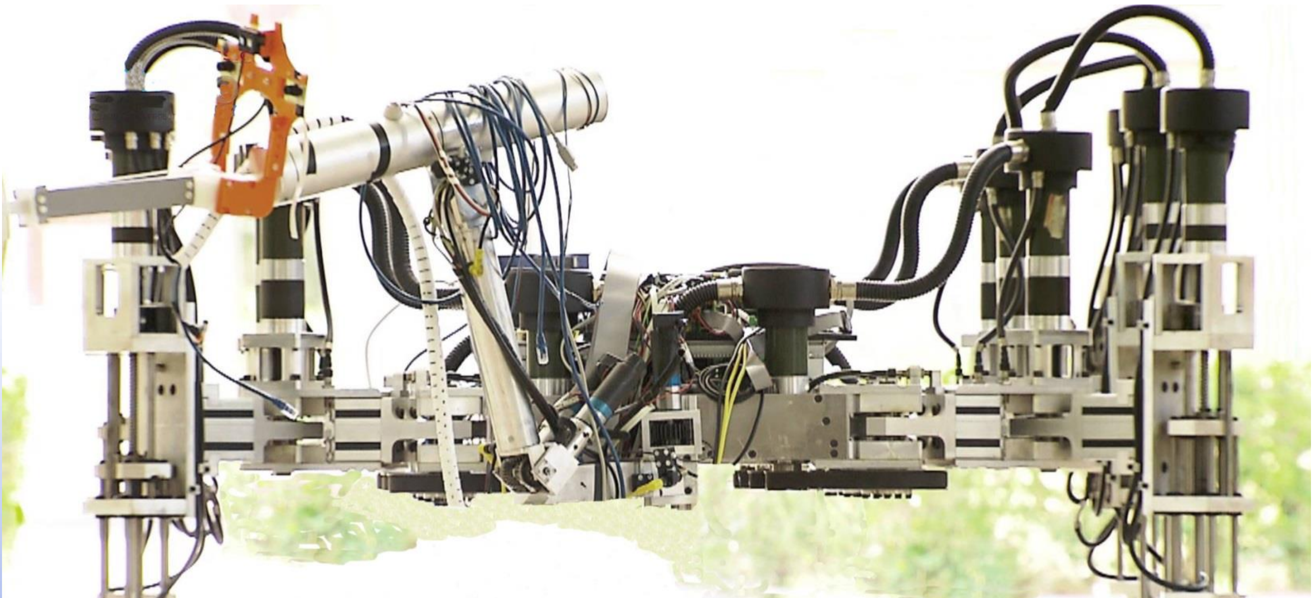

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CHAPTER 38

PEDESTRIAN MOTION PREDICTION: A GRAPH BASED APPROACH

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A novel pedestrian motion prediction technique is presented in this paper. Its main achievement regards to none previous observation, any knowledge of pedestrian trajectories nor the existence of possible destinations is required; hence making it useful for autonomous surveillance applications. Prediction only requires initial position of the pedestrian and a 2D representation of the scenario as occupancy grid. First, it uses the Fast Marching Method (FMM) to calculate the pedestrian arrival time for each position in the map and then, the likelihood that the pedestrian reaches those positions is estimated. The technique has been tested with synthetic and real scenarios. In all cases, accurate probability maps as well as their representative graphs were obtained with low computational cost.

1 Introduction

Nowadays, the need of improving the surveillance and security systems in critical infrastructures has led to develop novel strategies that minimize security weaknesses and provide solutions for responding efficiently and on-time to potential threats. In this sense, human motion prediction arises as a powerful tool to enhance the detection capabilities and reaction in possible presence or approximation of intruders to restricted or vulnerable locations. For these reasons, in this paper a novel approach for pedestrian motion prediction that can be used in any given scenario with the minimum requirements of situational information is presented.

Most of previous work on pedestrian motion prediction has been focused on identifying motion patterns from previous observations, and then, those patterns are used to predict future trajectories or goals (Kitani et al., 2012). Nevertheless, that is not an option in security applications where it is needed to model behaviors that differ from the common situations. Other approach employs the sub-goal concept to model and predict the pedestrian behavior (Ikeda et al., 2013). In this case, the scenario is discretized in a set of sub-goals that can be reached by the pedestrian. Unfortunately, the sub-goals are also obtained from the analysis of large set of pedestrian trajectories. Regarding to the sub-goal approach, previous work was developed in order to obtain a topological representation of an unknown environment (Ramaithitima et al., 2016). Although, it is not necessary the previous knowledge to build the map, it discards a lot of information due to its reduced representation of the scenario as a single path. In this sense, the construction of a topological map could be employed to define the sub-goals and subsequently these sub-goals might be used to calculate a probability distribution and to predict the displacement of the pedestrian in the scenario.

The main novelty of this work is that it does not require any previous observation of pedestrian trajectories nor possible goals to estimate the likelihood that the pedestrian reaches any location in the map, including in long-term predictions. Also, due to the technique only needs the map of the scenario and the pedestrian position as inputs, it can be easily implemented in large infrastructures with different kind of security resources.

The rest of the paper is organized as follows: the methodology overview and the main process involved in the technique are presented in Section 2. The experiments and results of the methodology implementation are discussed in Section 3. Then, the conclusions of the work are provided in Section 4.

2 Methodology

The process starts when a new 2D representation of the scenario is received, the input for the algorithm can be defined as two-dimensional occupancy grid pictures as well as maps designed or acquired in the standard ROS (Robot Operating System) format. Then, the map is transformed into a representative cost-map that allows improving the efficiency of the other algorithms at the same time that it includes information about predefined behaviors of the pedestrians. The next step is performed by the Fast Marching Method and it includes the cost-map and the pedestrian position in order to obtain the arrival time of the pedestrian at each point in the map.

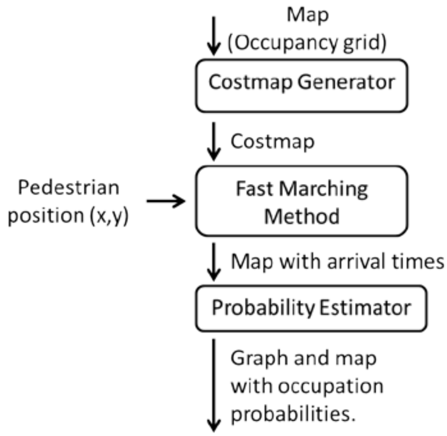

Fig. 1. Methodology overview.

Later, the map with the arrival times is used to generate an arrival time graph that corresponds to possible trajectories that can be followed by the pedestrian when he stands in the initial position. Finally, the graph is employed to calculate the probability distribution for the nodes and that distribution is translated into a new probability map. The methodology overview is shown in Fig. 1.

2.1 Cost-map generation

The cost-map is a modified representation of the original map that includes two main changes: scaling and distance transformation. The scale change refers to the increasing or decreasing the map resolution. In the proposed technique is desirable to reduce the number of pixels because the FMM and the probability estimator acts over the whole map and high resolutions could lead to a slow response in the algorithms. The scaling process is done by using a bilinear interpolation technique that ensures that the position in the resulting map have a correct translation to the original one.

From there, an increasing cost variation is added around the obstacles. This distance transformation allows modeling the behavior of pedestrians that move avoiding obstacles at the same time that stay away from the walls. In Fig. 2 is shown the cost-map representation of a hallway. In this case the original map was scaled from *0.05* to *0.35 m per pixel* and the distance transformation can be observed as a gray scale gradient near the walls.

2.2 Fast Marching Method

The required input for the FMM is a velocity map, so the cost-map obtained previously is transformed in a velocity map where the velocity achieved by the pedestrian at each position is directly proportional to the cost value in the same place. In order to simplify the case of study, it is assumed that the pedestrian will move continuously with a constant velocity over the unobstructed areas and he only will decrease the velocity when is close to the walls or obstacles.

Afterwards, the FMM (Sethian, 1999) is used to compute the amount of time that the pedestrian needs to reach each position in the map, and then, that information is employed to generate a new map that includes the arrival times. In Fig. 2 is shown the arrival time map obtained with the FMM when a pedestrian is located in the center of the hallway. In the image, blue pixels indicate near positions, red pixels refer to far places and yellow pixels are unreachable locations.

2.3 Probability estimation

The probability estimation algorithm is developed in two main steps: arrival time graph generation and probability distribution estimator. First, the values in the arrival time map are discretized. The set of discrete time values $T = \{t_1, t_2, t_3, \ldots, t_n\}$ is obtained by defining a constant time step from the pedestrian position to the farthest place in the map. So, the arrival time map is modified again by rounding its values to the larger nearest discrete value. This transformation allows clustering time connected positions; where the size of the cluster is directly proportional to the time step.

Next, a connected component labeling is performed in order to define a space-time differenced set of areas $A = \{a_1, a_2, a_3, \ldots, a_m\}$. This segmentation is realized with the aim of getting into the time clusters and dividing areas that can be reached in the same time (t_n) but they are not spatially connected (e.g. In a hallway, two opposite exits (a_1, a_2) could be reached in the same time (t_n), but they are not directly connected in the map) . After that, the arrival time graph is generated using the elements of A as nodes and the spatial connections between them as edges.

The discretized arrival time map and the corresponding arrival time graph are shown in Fig. 2. In this case, it was used a set of discrete time values composed by 10 elements: $T = \{t_1, t_2, t_3, \ldots, t_{10}\}$ that can be observed as opening circles that start in the pedestrian position (t_1) and end in the farthest points . Nevertheless, it was obtained a set of areas with 18 elements: $A = \{a_1, a_2, a_3, \ldots, a_{18}\}$, which means that some elements in A be-long to the same cluster in T (e.g. The elements (a_6,a_8) belongs to the same cluster (t_5)).

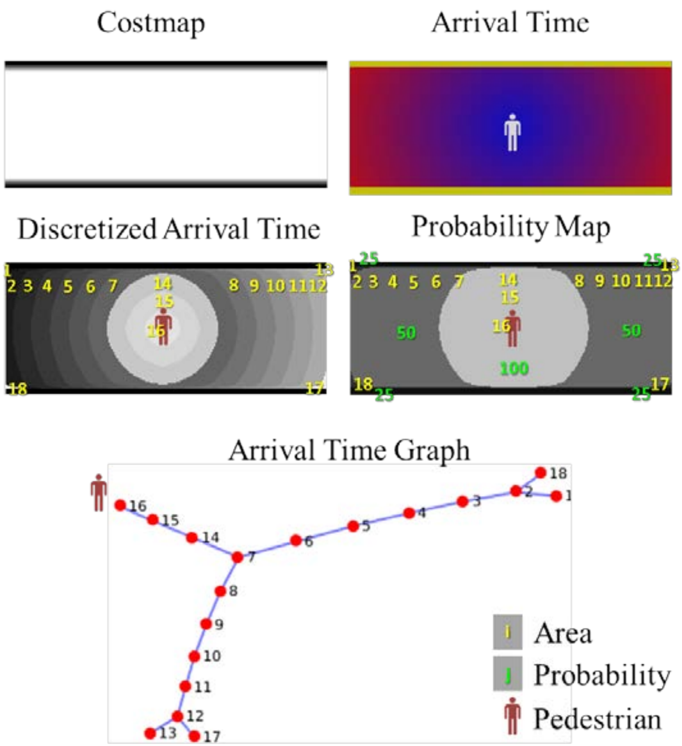

Fig. 2. Pedestrian motion prediction technique.

Table 1. Data from **Probability Map** and **Arrival Time Graph** in Fig. 2 .

Area	1	2	3	4	5	6	7	8	9
Prob. [%]	25	50	50	50	50	50	100	50	50
Area	10	11	12	13	14	15	16	17	18
Prob. [%]	50	50	50	25	100	100	100	25	25

Thereby, the probability estimation is easily achieved regarding the graph obtained above. The area that encloses the pedestrian position has *100%* of probability of being reached by the pedestrian. It is a normal assumption due to the closeness of the pedestrian to the positions included in this area. After that, if the parent node has only one child the probability is entirely passed to the next node, on the other hand, if the parent node has more than one child the probability is split and it is passed in equal parts to each child. In this point, a filtering process is performed in order to avoid the probability assignment for small areas. If the area (a_n) does not have the number of pixels over an arbitrary threshold, the area receives the same probability as its parent and it is not taken into account as a child for probability division. This distribution is iteratively done until all nodes in the graph are filled. The final probability assigned to each node is the sum of the probability given by its parents. (i. e. A node can have more than one parent). Finally, a new probability map is built using the information obtained in the last step. This map represents the likelihood that the pedestrian reaches any position in the scenario.

In Fig. 2 is shown the probability map. The probability values for each area are shown in the Table 1. In the picture, the pedestrian is located in the area (a_{16}), so this area has the *100%* of probability. Then, the areas (a_{15}, a_{14}, a_7) do not have siblings, so they receive the entire probability from their parents. The area (a_7) has two children (a_8, a_6), and the probability is split in equal parts and each of them receives the *50%*. Same situation can be observed in the areas (a_2, a_{12}).

3 Experiments and Results

The Simulated Map 1 is a room with a small free space in the middle, but with none entrance to go inside. From the start point, the pedestrian can achieve the other side of the room by two different trajectories, which means dividing the probability in two separate paths with *50%* each. Nevertheless, when the trajectories are joined in the other side, the probability fuses again and that area gets *100%*. In addition, it can be observed that the unconnected room in the middle is not taken into account in the prediction; due it cannot be reached by the pedestrian.

The Simulated Map 2 has the same scenario, but in this case the small space has two different entrances that can be reached by the pedestrian at different times. Thus, the new connections generated by the room entrances can be observed in the graph. First, the probability is completely passed from the area surrounding the pedestrian to its child. Then, there are three possible paths: up, center and down, so the probability is divided by three and each child receives a *33.3%*. Then, the center and down path are joined in the middle room, and the probability reaches the *66.6%*. Like in the previous experiment, the area in the other side of the room gets the *100%* as the sum of *33.3%* and *66.6%* provided by its parents.

The last experiment is the prediction technique applied in a real scenario. The map was built with a LIDAR sensor mounted over an Unnamed Ground Vehicle (UGV) and it is a 2D reconstruction of a street intersection. The graph and the probability map shows how the proposed technique can operate in non-trivial scenarios and it can make long-term predictions. The experiments and resulting maps and graphs can be observed in Fig. 3.

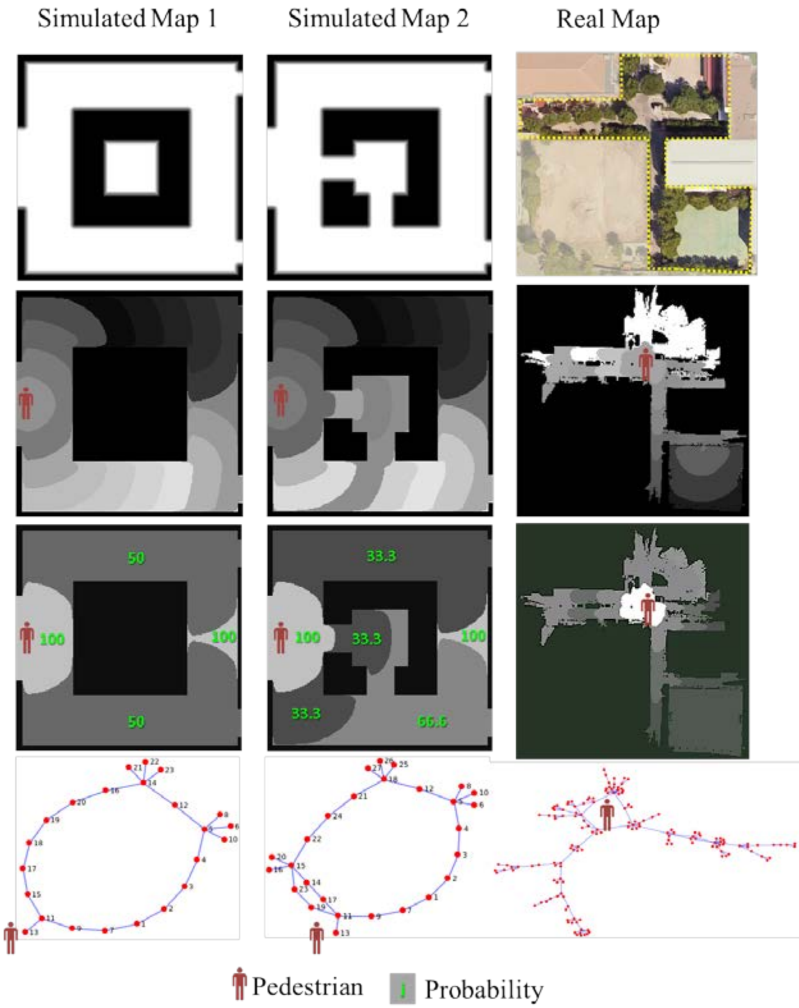

Fig. 3. Pedestrian motion prediction in simulated and real Scenarios.

4 Conclusions

An approach for pedestrian motion prediction was presented. The experiments and results show that it is possible getting probability estimations about the likelihood that the pedestrian reaches any position in the scenario, only using the pedestrian position and the map as inputs.

The proposed technique do not uses specific paths or possible destinations, so the calculations are made for the whole map. In this sense, an adequate cost-map generation is necessary in order to improve the performance of the FMM algorithm and the probability estimation.

A long-term prediction was acquired for large scenarios. Future works will be aimed to do an on-line implementation of the technique with a pedestrian in continuous motion as well as the integration of new information sources in order to get a better prediction in dynamic environments.

Acknowledgements

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